Comparison of Naïve Bayes, SVM, and Random Forest in Predicting the Job Waiting Time of Universitas Royal Alumni

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Abstract
Alumni job waiting time is a graduate-quality indicator in tracer studies, yet its use for prediction remains limited. This study compares Naïve Bayes, Support Vector Machine (SVM), and Random Forest in predicting the job waiting time of Universitas Royal alumni. The data come from the 2023–2025 tracer-study cohorts (598 alumni) with three waiting-time classes (0 months, 1–3 months, >3 months) and two feature scenarios: basic and extended (adding work region and job position). Processing was done in Google Colab using nested 5-fold cross-validation repeated 5 times and Friedman and Wilcoxon tests. With basic features the three algorithms were equivalent (macro-F1 0.373–0.383; p = 0.59). With extended features Random Forest was highest (macro-F1 0.412), followed by SVM (0.400) and Naïve Bayes (0.388), but the Friedman test was not significant (p = 0.14) and on the hold-out set SVM was slightly higher. Test-set accuracy (scenario 1/2): Naïve Bayes 49.17%/50.83%, SVM 47.50%/50.83%, Random Forest 50.00%/50.83%; baseline 54.17%. All models exceeded the majority-class baseline on macro-F1 (0.234). Job position and employer type were the most influential features. The findings are preliminary because the data are still a sample.

***Keywords**:* job waiting time; tracer study; Naïve Bayes; support vector machine; random forest

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Introduction

Tracer studies are used by universities to monitor how well graduates are absorbed by the labour market, and the time taken to obtain a first job is one of their main indicators [1], [2]. This information matters to program managers because it underpins curriculum evaluation, career services, and industry partnerships [2]. However, tracer-study data are usually reported only descriptively, while their ability to predict alumni waiting time has been little exploited.

Studies in Indonesia have applied data mining to predict alumni waiting time. Naïve Bayes was used for Computer Science alumni of Universitas Nusa Cendana with an accuracy of 81.82% [3], for Fasilkom Unsika alumni with 68.52% accuracy after backward-elimination feature selection [4], and for Universitas Sriwijaya alumni with 85.21% accuracy [1]. The C4.5 decision tree has also been used [5], and several studies built web-based information systems for this prediction [6], [7]. Internationally, graduate employability prediction has been examined with a variety of algorithms [8], [9], [10] and summarised in systematic reviews [11], [12].

Evidence on the best algorithm is not uniform. Naïve Bayes outperformed Decision Tree, K-NN, and Random Forest on Universitas Sriwijaya data [1], and C4.5 and Random Forest on Faculty of Psychology UIN Jakarta data, although its accuracy was only 53.96% [13]. In contrast, on data from the Faculty of Administrative Sciences, Universitas Brawijaya, the highest accuracy (84.73%) came from Decision Tree and SVM but largely reflected the majority class, the discriminative power of all models was low (AUC 0.50–0.579), and Random Forest gave the most balanced performance [2]. This shows that algorithm choice depends on data characteristics, and that accuracy alone is inadequate for imbalanced classes [14].

Based on the author's review of the 2021–2026 literature, several gaps remain. First, most waiting-time studies reviewed use a single algorithm or compare Naïve Bayes with tree-based methods [3], [4], [5], [1], [13], [6], [7]; SVM appears in only one of the studies reviewed, [2], which used a binary target (≤6 months or longer) at a faculty of a public university. Second, small computing colleges with several study programs (Information Systems, Computer Systems, Informatics Management, and Computer Engineering) have not been the subject of a comparison of these three algorithms. Third, evaluation often relies on accuracy from a single data split, whereas recent reviews point to inconsistent feature choices, a lack of standard datasets, and limited validation [12], as well as the need for contextual factors beyond skills [11].

This study aims to (1) compare Naïve Bayes, SVM, and Random Forest in predicting the job waiting time of Universitas Royal alumni in three classes, (2) test whether adding work-region and job-position features changes performance and the ranking of the algorithms, (3) evaluate the three algorithms more rigorously using macro metrics, a baseline, repeated nested cross-validation, and statistical tests, and (4) document the data-processing workflow in Google Colab so that it can be replicated as the data grow.

Literature Review

2.1 Tracer studies and job waiting time

Job waiting time is the time alumni take to obtain their first job after graduation, and it is the outcome variable in many tracer-study-based studies [1], [2], [3]. A systematic review of 20 studies found that data mining can serve as a decision-support tool for predicting employability, but predictor variables differ across countries and earlier studies mainly emphasised skills as the key factor [11]. The Universitas Brawijaya study concluded that tracer-study data are more useful for institutional diagnosis and service improvement than for predicting individual waiting times [2].

2.2 Previous studies on waiting-time prediction

Table 1 summarises the alumni waiting-time studies reviewed. Results cannot be compared directly because the number of classes, the features, and the validation schemes differ.

Table 1. Summary of previous studies on alumni job waiting-time prediction (2021–2026)

Ref.	Object / data	Algorithm	Main finding
[3]	Computer Science alumni, Universitas Nusa Cendana; tracer-study questionnaire; 4 classes	Naïve Bayes	Accuracy 81.82%
[4]	Fasilkom Unsika alumni; 270 records after cleaning; fast/slow classes	Naïve Bayes; Naïve Bayes + backward elimination	Accuracy 67.78% rising to 68.52% with feature selection
[5]	Fasilkom Unsika alumni; 462 records (2016–2020 graduates)	C4.5; C4.5 + forward selection	Accuracy 60.74% rising to 80.37% with feature selection
[1]	Universitas Sriwijaya alumni; 4,734 records, 2021 tracer data	Naïve Bayes, Decision Tree, K-NN, Random Forest	Naïve Bayes best (85.21%); RF 84.04%
[13]	Faculty of Psychology, UIN Jakarta; 170 records after cleaning	Naïve Bayes, C4.5, Random Forest	NB 53.96%; RF 50.79%; C4.5 46.03%
[2]	FIA Universitas Brawijaya; 1,280 alumni, 2021–2023 cohorts; binary target	NB, C4.5, Logistic Regression, RF, SVM, Gradient Boosted Trees	Accuracy 66.49–84.73%; AUC 0.50–0.579; RF most balanced
[6]	Web-based information system (RAD method)	Naïve Bayes + Laplace correction	System results matched manual calculation
[7]	UnHar alumni; web system	Naïve Bayes	No accuracy figure in the abstract

2.3 Graduate employability prediction

A study on Malaysian Ministry of Education tracer data compared Logistic Regression, Random Forest, Naïve Bayes, SVM, XGBoost, and ANN; ANN gave the highest accuracy at about 80% [8]. A follow-up study on more than 4,000 graduates showed that feature selection and BERT embeddings raised accuracy from 79% to 88% [10]. For information technology graduates, Decision Tree reached the highest accuracy among Decision Tree, Gaussian Naïve Bayes, Logistic Regression, Random Forest, and SVM [9]. A recent review lists SVM, Decision Tree, Random Forest, and ensemble methods as common algorithms, with limitations including a focus on accuracy, inconsistent features, and limited longitudinal validation [12].

2.4 Naïve Bayes, SVM, and Random Forest

Naïve Bayes computes class probabilities using Bayes' theorem under the assumption that features are conditionally independent. Laplace correction is used to avoid zero probabilities [6], and recent variants have been developed to improve recall and F1 on multivariate data [15]. *Support Vector Machine* searches for a maximum-margin hyperplane, and kernel functions map data into a higher-dimensional space where it is easier to separate [16]. *Random Forest* builds many decision trees on bootstrap samples with random feature subsets and combines the predictions of all trees by majority vote. Class imbalance can affect all three and must be accounted for in evaluation [14].

Comparisons of similar classification algorithms have been reported on various datasets in Indonesia. Naïve Bayes has been compared with SVM for determining online shopping ratings [17], with K-NN for user satisfaction with an application [18] and for predicting helpdesk ticket resolution time [19], and with Random Forest for disease classification [20]. Random Forest has also been used together with decision trees to predict student achievement status [21], and on its own to predict unemployment [22] and app rank [23]. Gaussian Naïve Bayes has been used to predict scholarship eligibility [24], and SVM has been compared with

XGBoost in flood risk factor analysis [25]. This study applies the three algorithms to tracer-study data with a three-class waiting-time target.

Research Methodology

3.1 Research design

This is a quantitative study using supervised multiclass classification. The stages are data collection, data merging and cleaning, target and feature construction, data splitting, hyperparameter tuning, evaluation, statistical testing, and feature analysis. All stages were run in Google Colaboratory using Python.

3.2 Data

The data are three Excel files of Universitas Royal tracer studies for the 2023, 2024, and 2025 cohorts, each containing one sheet per study program (Information Systems/SI, Computer Systems/SK, Informatics Management/MI, and Computer Engineering/TK). After summary rows and rows without a student ID were removed, 1,482 alumni rows remained; 598 rows had waiting-time data and were used for modelling. The MI and TK programs appear only in the 2023 cohort because those programs no longer exist in later cohorts. Names, student IDs, and phone numbers were not used as features and are not stored in the output files. The data used are an initial sample and will be extended.

3.3 Variables and feature scenarios

Table 2 presents the study variables. Waiting time (months) is taken from the tracer-study item "obtained a job within ≤ 6 months? → in how many months", which is stored in the Excel files in the "<6" or ">6" column; no row is filled in both columns. The 3-month cut-off was chosen so that class sizes are not too unequal and was fixed before any model was run. Two feature scenarios were compared: Scenario 1 (abbreviated S1; five basic features, namely PRODI, TAHUN, JENIS_INSTANSI, F14, and F15) and Scenario 2 (abbreviated S2; the basic features plus WILAYAH and JABATAN, giving seven features). Both scenarios use the same data, target classes, and evaluation procedure; only the number of features differs. Free-text location and position entries were grouped using keyword rules. Missing F14 and F15 values (34 rows) were imputed with the mode of the training data inside the pipeline. All features come from entries made after alumni started working, so the model describes associations rather than prediction before graduation.

Table 2. Study variables

Variable	Role	Description / values
Waiting-time class	Target	Fast (0 months); Moderate (1–3 months); Long (>3 months)
PRODI	Feature (S1, S2)	SI, SK, MI, TK
TAHUN	Feature (S1, S2)	Tracer-study cohort: 2023, 2024, 2025
JENIS_INSTANSI	Feature (S1, S2)	Private, Government, Self-employed, Non-profit/NGO, State-owned (BUMN/BUMD), Other, Unknown
F14	Feature (S1, S2)	Tracer-study questionnaire code: relatedness of field of study to job (scale 1–5)
F15	Feature (S1, S2)	Tracer-study questionnaire code: fit of education level to job (scale 1–4)
WILAYAH	Feature (S2)	Asahan/Tanjung Balai, Other North Sumatra, Outside North Sumatra, Other, Unknown
JABATAN	Feature (S2)	Administration/Staff, Service/Sales, Educator, Technical/IT, Other, Unknown

3.4 Data processing in Google Colab

Table 3 describes the processing steps implemented in the accompanying Google Colab notebook. Each step corresponds to one notebook cell, so all figures in the results section can be regenerated by running the notebook from the beginning (Runtime → Run all).

Table 3. Data-processing steps in Google Colab

No.	Process	Function / library	Output
1	Import libraries and set seed (42)	pandas, numpy, matplotlib, scikit-learn, scipy	Environment ready
2	Upload the three Excel files	google.colab.files.upload()	Data_Tracer_2023–2025 files
3	Merge all study-program sheets; find the "NIM" header row; keep rows with a numeric student ID; add TAHUN and PRODI columns	pandas.ExcelFile, concat	1,482 alumni rows
4	Build waiting time from the "<6" and ">6" columns; remove rows without waiting-time data and duplicate IDs; build three classes	pandas fillna, drop_duplicates	598 rows
5	Normalise employer type, region, and position into standard categories	Keyword rules (regex)	Categorical features
6	Stratified 80:20 train/test split	train_test_split(stratify=y)	478 train / 120 test
7	Pipeline: mode imputation then one-hot encoding	ColumnTransformer, SimpleImputer, OneHotEncoder	Feature matrix
8	5-fold hyperparameter tuning, macro-F1 score, training data only; evaluate on the test set and compare with the baseline	GridSearchCV, classification_report	Best parameters; hold-out table
9	Repeated nested cross-validation (outer 5-fold × 5, inner 3-fold)	RepeatedStratifiedKFold, cross_validate	Mean and standard deviation
10	Friedman and Wilcoxon tests on per-fold macro-F1	scipy.stats	p-values
11	Permutation importance for Random Forest; export results without personal data	permutation_importance, to_csv	Feature ranking; CSV files

3.5 Models and evaluation

Naïve Bayes used MultinomialNB on one-hot features with a search space of alpha {0.1; 0.5; 1.0; 2.0} and fit_prior {True; False}. SVM used SVC with balanced class_weight, kernel {linear; RBF}, C {0.1; 1; 10; 100}, and gamma {scale; 0.1; 0.01}. Random Forest used 200 trees with balanced_subsample class weights, max_depth {None; 5; 10}, and min_samples_leaf {1; 2; 5}. Evaluation metrics were accuracy and macro-averaged precision, recall, and F1, i.e. the simple average over classes so that minority classes carry equal weight. The baseline always predicts the majority class. Because the test set contains only 120 alumni, the main comparison uses repeated nested cross-validation. Differences between models were tested with the Friedman test (three models) and paired Wilcoxon tests; p-values from overlapping folds tend to be optimistic and are therefore treated as indications.

Results and Discussion

4.1 Data characteristics

Table 4 shows the class distribution. 54.0% of alumni reported starting work immediately (0 months); the median waiting time was 0 months, the mean 1.70 months, and the maximum 19 months. The SI program dominates the data (499 alumni), while MI and TK have only 7 and 6 alumni. Most alumni work in Asahan/Tanjung Balai (444 alumni) and in administration/staff positions (268 alumni).

Table 4. Waiting-time class distribution by cohort

Cohort	Fast (0 mo)	Moderate (1–3 mo)	Long (>3 mo)	Total
2023	97	59	57	213
2024	119	40	40	199
2025	107	52	27	186
Total	323 (54.0%)	151 (25.3%)	124 (20.7%)	598

4.2 Best hyperparameters

In Scenario 2, grid search on the training data (478 alumni) selected Naïve Bayes with alpha=0.1, fit_prior=False (CV macro-F1 0.409), SVM with C=100, gamma=scale, kernel=rbf (0.411), and Random Forest with max_depth=None, min_samples_leaf=5 (0.402). In Scenario 1, SVM chose a linear kernel with C=0.1 and Random Forest a maximum depth of 5; in Scenario 2 SVM chose an RBF kernel and Random Forest no depth limit.

4.3 Test-set performance

Table 5 summarises the accuracy of each method in Scenario 1 (basic features) and Scenario 2 (extended features), on both the test set and repeated cross-validation.

Table 5. Accuracy (%) of each method by scenario (S1 = basic features; S2 = extended features)

Method	Test set S1	Test set S2	Cross-validation S1	Cross-validation S2
Naïve Bayes	49.17	50.83	42.41	46.02
SVM	47.50	50.83	42.24	44.48
Random Forest	50.00	50.83	41.64	47.72
Baseline (majority)	54.17	54.17	54.01	54.01

Table 6 presents performance on the 120 test alumni. In both scenarios all models exceeded the baseline on macro-F1 (0.234), but none exceeded the baseline accuracy (54.17%), because the baseline is always right on the majority class, which makes up more than half of the data. In Scenario 1 Naïve Bayes was highest (macro-F1 0.439); in Scenario 2 all three had equal accuracy (50.83%) and SVM was slightly highest on macro-F1 (0.470). The model order on the test set differs from the order in repeated cross-validation (Section 4.4).

Table 6. Model performance on the test set (20%, n = 120) (S1 = basic features; S2 = extended features)

Scenario	Model	Accuracy	Precision (macro)	Recall (macro)	F1 (macro)
S1	Baseline (majority)	0.5417	0.1806	0.3333	0.2342
S1	Naïve Bayes	0.4917	0.4393	0.4422	0.4390
S1	SVM	0.4750	0.4099	0.4074	0.4070
S1	Random Forest	0.5000	0.4343	0.4309	0.4321
S2	Baseline (majority)	0.5417	0.1806	0.3333	0.2342
S2	Naïve Bayes	0.5083	0.4543	0.4585	0.4552
S2	SVM	0.5083	0.4707	0.4726	0.4697
S2	Random Forest	0.5083	0.4528	0.4503	0.4499

Per-class analysis in Scenario 2 (Figure 1) shows that the “Fast” class is easiest to predict (F1 0.613–0.646), the “Moderate” class lies at F1 0.364–0.388, and the “Long” class is hardest

(F1 0.340–0.408; recall 0.320–0.400). The models therefore remain weak at identifying alumni who wait more than three months, even though this group is the most relevant to career services.

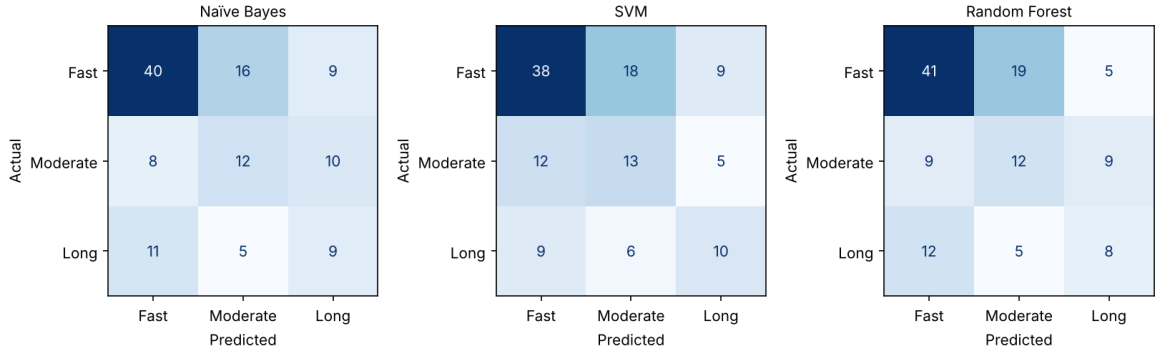


Figure 1. Confusion matrices on the test set, Scenario 2: (left) Naïve Bayes, (middle) SVM, (right) Random Forest

4.4 Repeated nested cross-validation

Table 7 presents the results of nested 5-fold cross-validation with 5 repeats (25 folds) on all data. In Scenario 1 the three models are nearly equal (macro-F1 0.373–0.383). In Scenario 2 the ranking becomes Random Forest (0.412), SVM (0.400), then Naïve Bayes (0.388); the accuracy of Random Forest, 47.72%, is also highest but remains below the baseline accuracy (54.01%).

Table 7. Repeated nested cross-validation results (mean ± standard deviation, 25 outer folds) (S1 = basic features; S2 = extended features)

Scenario	Model	Accuracy	Precision (macro)	Recall (macro)	F1 (macro)
S1	Baseline (majority)	0.5401 ± 0.0019	0.1800	0.3333	0.2338 ± 0.0005
S1	Naïve Bayes	0.4241 ± 0.0369	0.3956	0.3943	0.3828 ± 0.0411
S1	SVM	0.4224 ± 0.0505	0.3902	0.3921	0.3806 ± 0.0478
S1	Random Forest	0.4164 ± 0.0328	0.3817	0.3805	0.3726 ± 0.0337
S2	Baseline (majority)	0.5401 ± 0.0019	0.1800	0.3333	0.2338 ± 0.0005
S2	Naïve Bayes	0.4602 ± 0.0411	0.3951	0.3964	0.3880 ± 0.0420
S2	SVM	0.4448 ± 0.0411	0.4061	0.4066	0.3995 ± 0.0452
S2	Random Forest	0.4772 ± 0.0381	0.4166	0.4148	0.4123 ± 0.0341

4.5 Statistical tests

Table 8 shows that in Scenario 1 there is no difference among the models (Friedman $p = 0.59$). In Scenario 2 the Friedman test is also not significant ($p = 0.14$); Random Forest outperformed Naïve Bayes in the paired test ($p = 0.020$, winning 16 of 25 folds), but this value is no longer significant after Bonferroni correction for three comparisons (threshold 0.017), and overlapping folds make the p-value optimistic. Adding features (Scenario 2 versus 1) raised the macro-F1 of Random Forest by 0.040 (21/25 folds, $p < 0.001$), but not significantly for SVM (+0.019; $p = 0.16$) or Naïve Bayes (+0.005; $p = 0.49$).

Table 8. Statistical tests on per-fold macro-F1 (S1 = basic features; S2 = extended features)

Scenario	Test	Comparison	F1 difference	Wins/Total	p
S1	Friedman (3 models)	NB vs SVM vs RF			0.595
S1	Wilcoxon	NB vs SVM	+0.0021	12/25	0.916
S1	Wilcoxon	NB vs RF	+0.0102	16/25	0.156
S1	Wilcoxon	SVM vs RF	+0.0080	13/25	0.491
S2	Friedman (3 models)	NB vs SVM vs RF			0.141
S2	Wilcoxon	NB vs SVM	-0.0115	8/25	0.173
S2	Wilcoxon	NB vs RF	-0.0243	9/25	0.020
S2	Wilcoxon	SVM vs RF	-0.0128	11/25	0.210
S2 vs S1	Wilcoxon	Naïve Bayes	+0.0052	12/25	0.491
S2 vs S1	Wilcoxon	SVM	+0.0188	14/25	0.165
S2 vs S1	Wilcoxon	Random Forest	+0.0397	21/25	< 0.001

Note: F1 difference = first model minus second model (for S2 vs S1, S2 minus S1); wins/total = number of folds in which the first model is higher.

4.6 Most influential features

Table 9. Permutation importance of Random Forest, Scenario 2, on the test set (decrease in macro-F1)

Feature	Decrease in macro-F1	Standard deviation
JABATAN	0.0410	0.0343
JENIS_INSTANSI	0.0360	0.0365
WILAYAH	0.0231	0.0177
F15	0.0154	0.0144
TAHUN	0.0048	0.0278
F14	-0.0074	0.0321
PRODI	-0.0185	0.0133

Job position (0.041) and employer type (0.036) are the most influential features, followed by region (0.023). Other features have small or negative values, and for many features the standard deviation is equal to or larger than the value; PRODI is negative. These findings are exploratory and do not indicate cause and effect.

4.7 Discussion

This discussion compares two feature scenarios. Scenario 1 (S1) uses the basic features: study program, cohort, employer type, F14, and F15. Scenario 2 (S2) uses the basic features plus work region and job position. The data, target classes, and evaluation procedure are the same for both scenarios.

Scenario 1 (basic features). In repeated cross-validation, accuracy was 41.64% for Random Forest, 42.41% for Naïve Bayes, and 42.24% for SVM. On the test set, accuracy was 50.00% for Random Forest, 49.17% for Naïve Bayes, and 47.50% for SVM. That is, the three methods classified the waiting-time class correctly for about 42% of alumni in cross-validation and 47.50–50.00% on the test set, with a difference among methods of less than 1 percentage point in cross-validation. The macro-F1 of the three models ranged from 0.373 to 0.383, and the Friedman test showed no difference ($p = 0.59$).

Scenario 2 (extended features). In repeated cross-validation, accuracy was 47.72% for Random Forest, 46.02% for Naïve Bayes, and 44.48% for SVM. On the test set, all three were

equal at 50.83%. That is, in cross-validation the three methods were correct for about 44–48% of alumni, with a difference among methods of up to 3.24 percentage points. On macro-F1, Random Forest was highest in repeated cross-validation (0.412) and SVM was highest on the test set (0.470); the Friedman test was not significant ($p = 0.14$).

Scenario 2 compared with Scenario 1. From Scenario 1 to Scenario 2, cross-validation accuracy rose by 6.08 percentage points for Random Forest (41.64% to 47.72%), 3.61 points for Naïve Bayes (42.41% to 46.02%), and 2.24 points for SVM (42.24% to 44.48%). On the test set, accuracy rose by 0.83 points (Random Forest), 1.66 points (Naïve Bayes), and 3.33 points (SVM). In macro-F1, the increase for Random Forest was 0.040 (21/25 folds), whereas the increases for SVM (+0.019) and Naïve Bayes (+0.005) were not statistically evident. In both scenarios and in every evaluation, the accuracy of the three models was below the baseline accuracy (54.17%), whereas the macro-F1 of all models was above the baseline (0.234). The "Long (>3 months)" class was hardest to predict for all models, and job position and employer type gave the largest decrease in macro-F1 in the permutation-importance analysis. For reference, the accuracy of the UIN Jakarta study ranged from 46.03% to 53.96% [13] and that of the Universitas Sriwijaya study from 84.04% to 85.21% [1].

The limitations of this study are: (1) the data are still a sample; (2) all features were measured after alumni started working; (3) GPA, length of study, internships, and language ability are not yet available; (4) the number of MI and TK alumni is very small and comes only from the 2023 cohort; (5) the class cut-offs and the region and position grouping rules were set by the researcher; and (6) the meaning of codes F14 and F15 follows the author's assumption and needs confirmation with the tracer-study administrators.

Conclusion

This study compared Naïve Bayes, SVM, and Random Forest in predicting three classes of job waiting time for 598 Universitas Royal alumni in two scenarios: Scenario 1 (basic features) and Scenario 2 (basic features plus work region and job position). Test-set accuracy for Scenario 1 and Scenario 2 was 49.17% and 50.83% (Naïve Bayes), 47.50% and 50.83% (SVM), and 50.00% and 50.83% (Random Forest), respectively. In repeated cross-validation, the macro-F1 of Scenario 1 was 0.373–0.383 with no evident difference among models, and in Scenario 2 Random Forest was highest (0.412) compared with SVM (0.400) and Naïve Bayes (0.388), with a non-significant Friedman test ($p = 0.14$). All models were above the baseline on macro-F1 and below it on accuracy. The "Long (>3 months)" class was hardest to predict, and job position and employer type were the most influential features. Future work includes adding data and academic and experience features (GPA, length of study, internships, language ability) when available.

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